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Supporting Design Problem-exploring with Emergent Technologies

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Abstract

The goal in this study is to highlight the value of using emergent technologies to support human effort in identifying creative design problems. First, we explore the relationship between design and creativity - a popular concept and an important requirement in engineering design process. A search is conducted across repositories. This includes search in Google, Google Scholar and Google Books databases in addition to others. Findings show that the extent to which the design process requires creativity is somewhat obscure and not generally perceptible. We observe that creativity consists of two aspects: problem-solving and problem-exploring. We also observe that creativity drives the design process, not by the way of problem-solving but by the way of problem-exploring. However, currently, focus is on problem-solving than the equally important problem-exploring. For every 135 studies on problem-solving, there is only one on problem-exploring. Study on problem-exploring is limited. We research further and identify some determinants of the neglect in problem-exploring in design. These determinants are lack of motivation, significant level of difficulty and the presence of many problems yet unsolved. Using the X-Design Process model and Problem-dependent Solution model we show the importance and benefits of problem-exploring in design and why it deserves attention. Consequently, we illustrate the use of emergent technologies to support problem-exploring in design and give reasons why this is possible in Industry 4.0. These technologies include data mining, natural language processing, machine learning, duplication recognition, and so on. We indicate that these technologies will only play subordinate role to humans towards inspiring problem-exploring in design. Also, we state that a precondition to applying these technologies is a study of the human problem-exploring cognition process for subsequent simulation. Success in computational problem-exploring would lead to breakthroughs in global problem-exploring and trigger more creative solutions in coming years.

Keywords: Creativity; Design Process; Industry 4.0; Problem-exploring

Glossary

Aspiration space in design refers to a set of goals which the design should achieve [1]. Such goals are framed by the design team's wishes [2]. A client can be part of a design team.

Design space exploration means searching design alternatives prior to implementation [3]. It entails removing unsatisfactory concepts based on predefined design goals and bounds.

Feasible space in design is framed by unconditional requirements which a design is bound to satisfy [1].

Fixation is a state of mind in which prior ideas or solutions constrain the thoughts to produce better ideas or solutions [4].

Problem-exploring or problem-finding is the process of (re)searching and identifying problems [5]. In this study, we adopt 'problem-exploring' because it reflects the wider scope in finding problems. Hence, problem-exploring in design encompasses all actions towards identifying a design problem.

Satisficing in design refers to selecting an option that meets design requirements rather than optimal solution [6].

Solution space in design is a set of all feasible solutions that satisfies a particular problem framing [7].

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1. Introduction

Humankind is witnessing the fourth industrial revolution (Industry 4.0). It is a new sphere of industry characterized by new emergent digital and internet technologies with the potential to expand to other spheres of industry [8]. Albeit the implementations of the emergent technologies are not fully certain [9], it is envisaged that Industry 4.0 would have a great impact on design. According to Crawford [10], Industry 4.0 will have a disruptive impact on design process. This is not surprising because there is a strong link between design and manufacturing as evidenced by some already established concepts such as – CAD/CAM, DFMA, QFD and so on. Design itself is a bridge between creativity, innovation and invention [11]. It is a creative process that materializes ideas [12]. Albeit design is universal and applies to different areas such as architecture, art, fashion and so on [13], but it is the foci in engineering [14]. The engineering design process is a pathway from idea to reality [15]. According to Lueptow [16], the design process consists of three key elements - design specification, ideation and detail design. The design process creates a *solution space* through ideation and applies *satisficing* in the *design space exploration* that leads to a final concept selection based on pre-established *feasible* and *aspiration spaces*.

Engineering design process requires creativity [17,18,19]. There are many definitions of creativity [20]. Unlike the word 'energy' – generally defined as the ability to do work, there is no uniform agreement in the definition of the word 'creativity' among scholars [20,21,22]. However, a precise definition of creativity is as important as any in-depth study in the area [23]. Hence, we define creativity in the next section. The extent to which the design process requires creativity is somewhat obscure and not generally perceptible. Creativity is made up of two aspects: problem-solving and problem-exploring [24]. Currently, focus is on the former than the latter [24,25,26]. In this study, we investigate the lack of focus on the problem-exploring aspect of creativity and the causative factors. Sequel to this, we propose the use of emergent technologies to support problem-exploring in engineering design. To achieve this, we perform a search across repositories to ascertain the extent of research towards problem-exploring. Also, we study different emergent technologies to identify those with potential for application in problem-exploring. Problems exist in different sectors - economic, education and so on. However, in this study, we focus on problem-exploring in engineering design.

In Section 2, the definitions of creativity and problem are presented and the study knowledge gap. Followed by explanations of the three key design process activities, and how problems drive design in Section 3. The lack of attention on problem-exploring and the determinants are discussed in Section 4. In Section 5, the emergent technologies under Industry 4.0 with potentials to support problem-exploring are discussed. The study is concluded in Section 6.

2. Creativity, problem and problem-exploring

What is Creativity in design? We define creativity as a self-initiated process of a system that draws extensive information from society to create or identify problems and/or ideas that solve problems. The system here could be human or computational devices. Creativity has many definitions. For instance, creativity is described as a process that involves interaction among aptitude, process, and environment used by a person or group to produce a noticeable product accepted as being both novel and useful by the society [27]. Creativity has an essence of nature [28]. According to Wilson [29], creativity is the search for originality initiated in the human mind; an expression of humans' natural love for novelty. As put by Wyse and Dowson [30], creativity is a person's ability to produce the following: new or original ideas, insights, restructurings, inventions, or artistic objects in a way that suitably qualified persons can agree to its scientific, aesthetic, social, or technological usefulness. As explained by Lau [31], creativity as the ability to come up with novel ideas that are also valuable requires a database of knowledge. Creativity is employed in the process of problem-solving to generate alternative ideas that can solve the problem.

What is a Problem in design? According to Runco [32], a problem is a situation with a goal and a hindrance to the goal. In design, problem is the difference between a present state and an aspired or imagined state [33]. It is an inevitable and pervasive part of life [34]. Problems can either be created or solved in the course of human interactions and can transform from one form to another. The word 'problem' has a negative connotation in general. The occurrence of problems is usually prevented or avoided in many occasions. However, it is argued that problems are not always associated with something erroneous, a hindrance or something that needs to be fixed [35]. As a support to this, Treffinger [36] suggests that a problem could be "any important, open-ended, and ambiguous situation for which one wants and needs new options and a plan for carrying a solution successfully." Problem activates thinking towards solutions. It inevitably becomes obvious whenever the way to reach a goal is unknown and movement from a given situation to a desired situation by action is impossible [37]. According to Getzels [25], there are three types of problems: 1) presented problem, 2) discovered problem and 3) created problem. Presented problem refers to a problem that exists and already has a formulation, method of solution and solution irrespective of whether this information is known to whom the problem is given or not. Discovered problem is a problem that exists with or without an existing formulation, method of solution, or solution and noticed by oneself rather than being given to one. Created problem refers to a problem that was never a problem, at least one that poses a threat to human existence, until someone made it an apparent problem.

Can a new design problem be explored computationally? This is a knowledge gap question. In the diverse definitions of creativity, as we reviewed, the terms 'novelty,' 'originality,' and 'something new' are common implicit and explicit occurrences. Creativity is equally required in both problem-solving and *problem-exploring*. It accounts for majority of new discoveries. However, the general understanding that a discovered problem is creative, 'something new' or 'novel' lacks. It requires significant creative thinking to discover a new problem and to make an unfamiliar problem an obvious one [38]. Some problems would remain uncreated or undiscovered without exercising a certain degree of creative reasoning.

Despite its importance, problem-exploring is not prevalent in both study and practice, especially the latter as shown in Section 4. In the same section we show that one of the possible reasons for the non-prevalence of problem-exploring in design is the inherent difficulty in the process in practice. The process solely relies on human creative effort with no dedicated external support tool. We propose that the deployment of computational technologies in problem-exploring would play an assistive role in easing the difficulty involved in the process. Also, such deployment would serve as a proactive measure in intentionally initiating the identification of problems than leaving it to accidental discovery which has implications on the rate at which solutions are found. A relatively easy problem-exploring process would attract more involvements. This allows for more proactive problem discoveries leading to increased local and global solutions in the field of engineering design with significant economic potentials [39,40,41]. Now, emergent Industry 4.0 technologies offer potentials for applications in problem-exploring which before was not possible.

3. Design Process

The design process is a problem-solving process used for solving identified design problems. As illustrated previously, design process consists of three key activities – design specification, ideation and detail design. The decisions made during the design process have economic potentials [39,40]. For instance, design accounted for £85.2 billion in gross value added (GVA) in the UK in 2016. This value represents 7% of the UK GVA for that year [41]. Wrong design decisions lead to economic waste of over 70% of the total cost of any design project [42]. The three key activities of the design process are central to many design and product development models including [43,44,45].

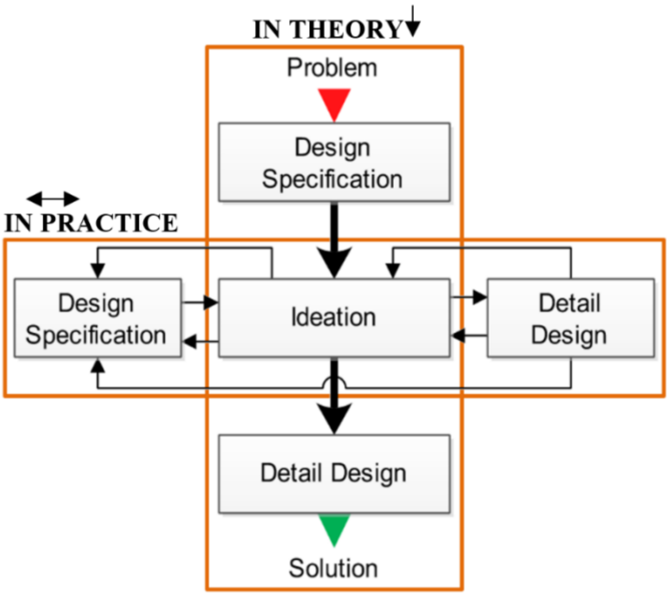


Fig. 1. The X-Design process

What drives the design process? Design is an activity practiced within a framework that incorporates conventional engineering topics [43]. It uses stated objectives or design specification to deliver products that satisfy users' needs [46].

Following the review of some design process models, we propose a design approach, the X-Design process (Cross design process), as shown in Fig. 1. The design process has a theoretical order of flow or hierarchy (vertical flow or sequential process) for which there is no strict adherence in practice (horizontal flow or concurrent process) [47]. The identification of a problem initiates the design process – which does not start until a problem is either created, discovered or presented. Creativity drives the design process, not by the way of problem-solving but by the way of problem-exploring. The design process receives a problem at one end, solves it within the process and produces a solution at the other end.

Design specification, theoretically, is the first element of the design process. It is a formal document in design that contains the detailed information required for the entire design process activities [48, 49]. The design specification can be presented as a legal document. The other elements of the design process are carried out with the design specification as a guide or reference. Incorrect design specification could lead to engineering failures [50]. Some elements considered in design specification are existing patents, ergonomics and the "ilities" (sustainability, manufacturability and so on) [43,51,52,53,54].

Ideation or conceptual design deals with the generation and evaluation of concepts, and the selection and development of a final concept [55]. Theoretically, it is the second activity of the design process where creativity plays a very dominant role based on convergent-divergent thinking [56]. It largely relies on human thinking and involves complex psychological processes that may be difficult to describe. Ideation is based on the principle that a larger number of ideas has a higher probability of containing a better solution than a smaller number of ideas [57]. The last part of the ideation process involves a deliberate suppression of divergent thoughts, and the final concept selection and development. This last part is necessary, otherwise the design process runs in an endless loop of ideation, iteration or trial and error [58] which has implications on the product time to market (TTM).

Detail design, theoretically, is the third and last activity of the design process. It focuses on developing components and subsystems into details. Formal drawings are produced to standards. Inter-part associations and design information change propagations are checked [59]. The use of parametric CAD models become increasingly helpful [16,60]. Listed design specifications are thoroughly cross-checked at this stage before proceeding to manufacturing. Progressing beyond the detail design level of any product design locks in over 70% of the total project cost.

So far, by using the X-Design process model, we establish the importance of problem identification for the design process. In the next section we address why problem-exploring is lacking in design.

4. Why problem-exploring is not prevalent in design

Generally, there is a low focus on problem-exploring. This includes the area of design. In this study, by using google, we conduct a basic search for the exact phrases "problem solving", "problem finding", and "problem exploring." We discuss the result of this search below.

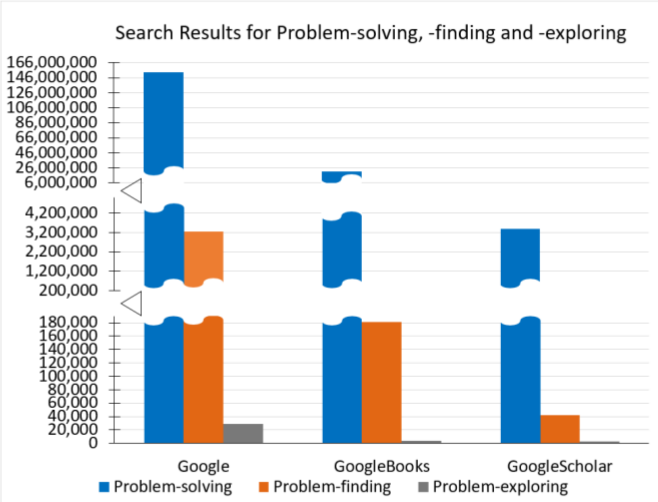


Fig. 2. Search Results for Problem-solving, -finding and -exploring

The result of the basic google search conducted is shown in Fig. 2. For the Google and Google Books searches, United Kingdom is selected in the Region Settings. For the Google Scholar search, library access link is permitted for the University of Liverpool. The details of the individual records of the search results are not verified. However, the result of this basic search is similar to that of related studies. For example, Abdulla and co-authors [61] conducted a search on divergent thinking, problem-solving and problem-exploring using six sources of publication databases. Their search result reveals that for every 135 studies on problem-solving, there is only one on problem-exploring. The result of the google search in this study also conforms to the statement made by Getzels [25] on the lack of attention on problem-exploring: "Despite the self-evident role of problems in initiating thought and the function of new problems in guiding thought toward new solutions, very little is known about how problems are found and formulated." As creativity is intricately connected to the human brain [62], we extended our search further to a compendium of researches on human brain in Ramachandran [63]. A search in Ramachandran for the words "problem-solving", "problem-finding" and "problem-exploring" shows over hundred and thirty (130), zero (0) and zero (0) occurrences, respectively. In addition, a google search for "computational problem-exploring system" did not return any verifiable result.

4.1. Determinants of problem-exploring lack in design

Having observed the low focus on problem-exploring, based on results of the researches conducted, we identify and present some reasons why problem-exploring is not prevalent. We discuss these reasons below.

Lack of motivation discourages individuals to engage in problem-exploring. Already, we establish that problem-exploring is an aspect of creativity and requires creativity (Sections 2). Studies show that motivation plays a very important role in encouraging creative abilities in humans [64, 65]. Problem-exploring abilities are ignored and attract no recognition compared with problem-solving abilities. In patents, identified problems are not recognized as discoveries or creative contributions [66]. As put by Runco [32]: "individuals who only identify important problems but do not solve them are probably much less likely to attain eminence when compared with individuals who successfully solve noteworthy problems." The habitual centering of creative concepts on problem-solving has created an imbalance between the problem-solving and problem-exploring aspects of creativity and has made the latter unpopular [67].

Presence of numerous problems yet unsolved affects the drive towards exploring for new problems. There are many design problems yet to be solved [68]. An assumption is that, as a result, problem-exploring may not be considered pressing since numerous existing problems require solutions. The presence of these numerous problems contributes to the concentration of attention on problem-solving and the consequent desertion of problem-exploring. However, in the context of existing problems, in Section 4.2 we address the question "are there really benefits in problem-exploring in design?"

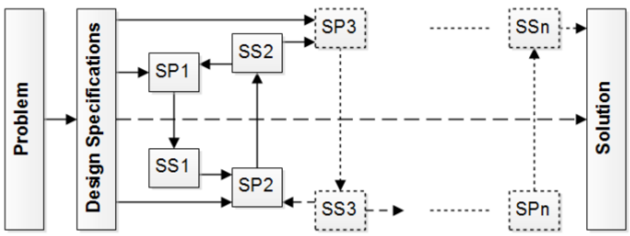
Difficulty in problem-exploring is implicitly revealed by studies. Problem-exploring requires significant degree of creativity [26] and coming up with creative outputs is difficult and challenging [40]. The study by Nicholl and Mclellan [69] suggests the people find it difficult to come up with creative ideas. Einstein and Infeld [38] suggest that problem-exploring is difficult and important: "The formulation of a problem is often more essential than its solution, which may be merely a matter of mathematical or experimental skill. To raise new questions, new possibilities, to regard old questions from a new angle, requires creative imagination and marks real advance in science." The effect of *fixation* affects ideation [70]. This effect is more on problem-exploring that it is on problem-solving. In problem-solving, features of existing solutions can be combined to obtain a new concept or solution. Boden [71] describes this process as combinational creativity. Han and co-authors [18] state that combinational creativity is relatively the easiest for humans compared with other types of creativity – exploratory and transformational. However, combinational creativity seldom applies in problem-exploring. When the task is to find a new solution, observing existing solutions for inspiration helps [72]. But, when the intent is to identify a new problem, it does not really assist to observe existing problems. Instead, significant level of creativity is employed to decipher the design problem solely on available information [73].

4.2. Why is problem-exploring important and beneficial in design?

Considering the determinants of problem-exploring lack in design, we present superseding reasons why problem-exploring in design needs attention. Hence, the need to address these determinants.

Proactiveness and skill support: Inventors usually solve problems discovered by themselves [74,75] albeit these problems have existed for a long time. It is of benefits to initiate a proactive discovery of these problems by making the process easy to get more people involved in problem-exploring. Discovering a problem early, prompts an early solution. It makes the problem available to those who could offer solutions to the problem. Hence, there is the need to sustain and encourage the problem-exploring abilities in individuals. This can be achieved by supporting avenues of getting more people involved in problem-exploring both in academia and industry. Now, the problem-exploring skills or abilities are on the verge of extinction due to lack of practice. All humans have creative skills [76]. However, some individuals are more problem-exploring oriented in creativity while some are more problem-solving oriented [32]. Creating or discovering a design problem is a challenging task and the skill or ability to do so needs support. In highlighting the importance of problem identification Polanyi [77] states that: "To recognize a problem which can be solved and is worth solving is in fact a discovery in its own right." If we do not proactively or deliberately explore for problems, some vital solutions would elude us.

Problem-dependent solutions: Some problems may not be effectively solved without the identification of other problems and their solutions [78,79]. This is common for the three types of problems – Created, Discovered and Presented illustrated previously. Hence, the solutions to the numerous existing problems may be tied to the discovery of new problems.



Please note that: **SP**: Sub-problem; **SS**: Sub-solution

Fig. 3. Problem-dependent solution model

In Fig. 3, we present the Problem-dependent Solution model proposed in this study. The abbreviations SP and SS stand for sub-problem and sub-solution, respectively. The integers 1, 2, 3…n represent the first (1), second (2), third (3) SP or SS to the last (n) SP or SS, respectively. The overall solution to a problem is impossible without solutions to its sub-problems first. The solution to some problems will not be obtained, at least accurately, until some other problems are solved; and to solve such problems they need to be found. An unknown problem stalls the solution, or leads to an unsatisfactory solution, to a problem that is dependent on the solution of the unknown problem. Hence, the crucial need for problem-exploring. In Fig. 3, broken borders are used to represent SP and SS that are unknown. For instance, since SP3 is unknown, it would be difficult or impossible to obtain an optimal solution to the main problem being solved. Also, due to the sub-problems, it is not possible to move directly from the main problem to the solution. This direct movement is represented with a horizontal broken line, from the design specification to the solution. The identification of a previously unknown problem could trigger unknown solutions. Lack of ideal solution to a problem leads to satisficing. In design, a large or complex problem can be decomposed into more manageable sub-problems [80]. In contrast, a problem without known sub-problems cannot be decomposed or effectively solved.

Increased inventive/creative solutions: New design problems often lead to inventive solutions [81,82]. Through problem-exploring, new design problems will be identified. This creates greater opportunity for the design process to produce unique or groundbreaking inventive solutions and not just innovative ones. A local problem identified in a given geographical region of the world could be a global solution impacting other regions. There are economic values in inventive design solutions. Hence, problem-exploring has local and global economic benefits for sustainable development [83].

Sustenance of the design process: Design problems feed the design process as illustrated with the X-Design process model, Fig. 1, Section 3. Since the design process depends on problems to produce solutions, there are benefits in identifying the design problems to be solved in the design process. So far, the importance of problem-exploring in design and reasons why it is not prevalent is discussed. In the next section, we present some Industry 4.0 technologies that can support problem-exploring, incite interests in the process and mitigate its non-prevalence, particularly due the inherent difficulties.

5. Industry 4.0 technologies and their assistive problem-exploring potentials in design

There are promising emergent digital and internet technologies in Industry 4.0 [84]. These technologies can assist humans in problem-exploring. According to Whitworth and Ryu [85], some tasks difficult for humans may be easy for computers and vice versa. Emergent computational technologies under Industry 4.0 present an opportunity for application in problem-exploring. Hence, we propose computational problem exploring, CPE - a process of discovering or creating problems based on the synergy of Industry 4.0 technologies. Computational technologies or systems have some advantages in problem-exploring over humans. For instance, they have better information retention memory, unvarying attentional abilities, incredible speed, higher information storage capacity and they do not obey physical laws which means they can work continuously and become extremely complex with limitless potentials [86]. The application of computational technologies in creativity for tasks that are difficult or beyond humans is acknowledged [87]. However, these technologies are applied in the area of problem-solving not in problem-exploring.

In the proceeding we show that the study and practice of problem-exploring is scarce. Partly, lack of support tools is responsible for this. In the following sections, we present some identified Industry 4.0 technologies with potentials to support problem-exploring in design such as machine learning, big data, natural language processing and so on. Further, we indicate why these technologies are relevant to problem-exploring in design by citing their current uses.

5.1. Big data

Big data is a concept that has attracted the attention of many researchers. According to Prasad [88], big data is "any voluminous amount of Structured, Semi-structured and Unstructured data that has the potential to be mined for information where the individual records stop mattering and only aggregates matter." Other definitions can be found in [89,90]. The highlight in these definitions is that the usefulness of big data lies in its mining or analyses values. These values are obtained through big data analytics - the process of gathering, structuring and exploring voluminous sets of data [91].

Relevance of big data to problem-exploring: To effect computational problem-exploring, enormous amount of data is a key requirement. Fortunately, such data is now available as big data. The massive data is generated continuously across different platforms such as blogs, websites, social media and so on. These data can be gathered and processed for problem-exploring. The data could be retrieved from different sources or crowdsourced by creating a dedicated social media/web platform for discussing problems encountered in diverse design-related fields. Using data mining and text mining technologies discussed in Section 5.2, the big data - which provides the foundation for data mining and text mining, can be explored for design problems.

Current uses of big data: Facilitated by efforts in machine learning and cloud computing, big data assists in the recognition or detection of duplicates in news articles [92,90]. Similarly, it is used to assist Drug Discovery - a process of finding a therapeutically useful compound in disease treatment and cure [93,94]. Due to big data, there is now the possibility of studying data as a whole, rather than as segregated exclusive sets, which helps big corporations such as Walmart, Amazon and Alibaba in gaining competitive business insights [95].

5.2. Data mining and text mining

Data mining and text mining are both aspects of big data analytics [91]. Data mining refers to the process of discovering information or patterns in structured data while text mining refers to the same process but for unstructured or semi-structured data [96,97,98]. According to Jin and co-authors [99], unpredictable information outside peoples' knowledge can result from data mining. The initial steps towards data mining and text mining involve carrying out a computer-automated or computer-augmented search on digitally stored data or big data using trawling and web crawling technologies [40,100,101,102,103,104].

Relevance of data mining and text mining to problem-exploring: A study by Getzels and Smilansky [105] concludes that different viewpoints and abstract thinking are preconditions to generating problems in a complex manner. Applying this in a modern context, data mining and text mining techniques can be employed in identifying design problems using the different viewpoints available in social media and other online platforms.

Current uses of data mining and text mining: Data mining is applied by Seah and Shim [100] in the detection of suicide intents from social media discussions. Other applications of data mining in social media are well documented [106,107]. Text mining is extensively used in the analysis of biomedical literature [108]. It is also used in Life Science for the efficient and automatic retrieval of information on phenotypes and habitats of microorganisms [104].

5.3. Natural Language Processing (NLP)

NLP refers to the study of language processing computationally [109]. It combines knowledge from computer science, artificial intelligence, and linguistics to make computers draw meaning from natural language input [110]. The need for NLP arose due to the emergence of big data in order to meaningfully process data from different sources [111]. Machine Learning (ML) technology is associated with NLP. ML is an area concerned with the 'learning' ability of computers [112]. It entails using algorithms to compel a computer program to make predictions about new data based on patterns inferred from examples or 'training' data [113].

Relevance of NLP to problem-exploring: Since computational problem-exploring, as we propose, involves the retrieval of data in its unstructured or semi-structured form, there is a need to process the data further using NLP. Texts (words) will be mined from the big data and processed using NLP. The processed words can be combined to frame a design problem or generate phrases that describe a design problem. Duplicates will be explored for the generated phrases in Google and Intellectual Property databases. The absence of duplicates will suggest that the phrase represents a valid design problem. This computational process is similar to the mental process required for identifying problems in design. However, the validation of a design problem depends on human judgement. Also, the presence of duplicates could suggest that the generated phrase is a problem if the duplicates are few or contain no solutions. Again, this depends on human judgement.

With further research and findings on human problem-exploring cognitive processes, ML technology can be used in 'training' machine systems to replicate the processes using data retrieved from mining. The data obtained can be normalized (by converting the attributes to binary form) using a set of mathematical processing and then run through a statistical process to determine when certain clusters of attributes occur together [114]. Machine systems can be 'trained' on problem-exploring. They can 'learn' how to frame a potential problem using word combinations. This could be based on the occurrence of keywords or word frequency. Machine systems can also be 'trained' on how to search for duplicates for the framed problems. Google provides various Kaggle datasets that could assist in the 'training' machine systems.

Current uses of NLP: Based on social media posts, NLP is applied to detect the mental state of individuals who made the posts in order to prompt intervention or support guide [115]. In predictive policing, NLP is employed in developing VeriPol – a computer-based tool with over 90% accuracy in predicting falsity in violent robbery reports based on the complaint texts [116]. Microsoft Word and Google search engine use NLP in detecting lexical and syntax errors in texts or words, and to make suggestions, while following some algorithms or referencing various datasets such as dictionary [117].

It is shown in the previous sections that the possibility exists in using computational technologies to retrieve data from several web-based platforms. The retrieved data can be processed using NLP and stored as a specific big data for problem-exploring. This specific big data can be mined to identify design problems that could be solved by the design process. Design problems can be randomly framed from the big data and verified for duplicates in expert-sourced databases such as Google Patent and Intellectual Property databases. Machine systems can 'trained' to carry out this procedure by employing ML technology. Verified design problems will be validated by humans. The decision process in validating these design problems can stimulate creative thinking towards creating or discovering another potential hidden design problem. In this study, we do not imply that computational systems are superior to humans in decision making. Instead, they can support human effort in identifying problems in design.

Computational problem-exploring constraints: In the implementation of the emergent Industry 4.0 technologies in problem-exploring, as we propose, there are envisaged computational and non-computational constraints. The programming of effective lines of codes for the data retrieval, processing and storage will present a level of computational challenge as these technologies have no previous applications in computational problem-exploring in design. The non-computational challenge includes obtaining the necessary permissions or authorizations to carry out web crawling in the process of the data retrieval and access some expert databases such as Google Scholar and Intellectual Property databases.

6. Conclusion

In this study, we draw attention to the possibilities of using computational technologies in Industry 4.0 to assist human effort in discovering design problems. The attention is drawn against the backdrop of the desertion of problem-exploring in design. We identified this desertion based on the literature search we conducted. The inherent difficulty involved in problem-exploring is amongst the determinants of its desertion in design. The reality that the design process depends on problems to produce solutions is obscure. To expose this fact, we propose the X-Design Process model. Amongst other supports provided, we highlight the importance of problem-exploring in design by proposing the Problem-dependent Solution model. The model is used to explain how problem-exploring can trigger previously unknown solutions in design and such solutions have economic benefits.

Until this point in time, action towards supporting problem-exploring or addressing the lack of its practice in design is not evident. Responsive solutions towards the lack of problem-exploring may have been stalled due to the lack of adequate technologies. As we show, Industry 4.0 computational technologies now offer possibilities to address the lack of attention on problem-exploring especially by playing a subordinate role to human effort in the process. These computational technologies include data mining, text mining, NLP and so on, which all employ the big data concept. The relevance of these technologies in problem-exploring, based on their current uses, is shown. Their specific desirable strengths in problem-exploring are also shown such as incredible speed, undivided attentional ability and so on.

Moving forward, in our further study, the human problem-exploring cognition process will be analysed. The understanding of the process is necessary for simulation purposes. It can help in developing an autonomous computational system for problem-exploring. Computational problem-exploring could be used to identify a potential design problem or stimulate creative thinking towards identifying a valid design problem. However, we state that computational problem-exploring is intended to support human effort in identifying problems in design. The output of such a system is still subject to human judgement in the foreseeable future. Success in computational problem-exploring would lead to breakthroughs in local and global problem-exploring and can trigger more creative solutions in the coming years. These solutions have economic benefits which support sustainable developments.

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